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Estimating net migration at high spatial resolution

Alessandrini, A.

Ghio, D.

Migali, S.

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Contact information
Name: Silvia Migali
Email: silvia.migali@ec.europa.eu

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Abstract

This technical report presents new estimates of net migration at high spatial resolution produced by the Joint Research Centre (JRC) – Knowledge Centre on Migration and Demography (KCMD). The development of new net migration data is the first step of a broader JRC project aimed at analysing the relation between climate change, population distribution and related migration.

The report uses demographic indirect estimation techniques based on population data from the JRC Global Human Settlement Layer (GHSL) to estimate five-year net migration from 1975 to 2015 at a spatial resolution of about 25 km. Notably, the recent definition of Degrees of Urbanization proposed by the European Commission and developed by the JRC is applied to distinguish net migration in urban and rural areas. Findings from the new datasets constitute the basis for further analyses on the relation between climate change and migration.

Two validation exercises of the new database are performed. First, when net migration estimates are aggregated from 25 km resolution to the country-level, a positive correlation with country net migration estimates from UN DESA is observed. Second, when focusing on Europe, the new estimates are coherent with Eurostat net migration figures at subnational (NUTS3) level.

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Authors

Alessandrini Alfredo, Ghio Daniela, Migali Silvia

1 Introduction

High spatial resolution data on net migration is needed to study a wide range of phenomena at disaggregated spatial scales. Net migration is defined as the difference between immigration and emigration[1]. In this report we provide data on net migration at high spatial resolution level, i.e. referring to areas of 25x25 km. This means that it is possible to identify whether these areas experience migration losses (i.e. have negative net migration) or migration gains (i.e. positive net migration). In other words, this spatial resolution allows us to analyse spatial movements at a granular and detailed level. One prominent example is the application of high spatial migration data for the analysis of the relationship between climate change and migration. Yet, collections of high spatial resolution demographic data are rare and their development at international level is at earliest stages. The most recent and unique example of net migration data at high spatial resolution and global coverage is constituted by the database developed by the Center for International Earth Science Information Network (CIESIN) for the period 1970-2010 (De Sherbinin, 2015). The first use of this database to study the nexus between climate change and net migration in different ecosystems can be found in the UK Government's Foresight Project, Migration and Global Environmental Change (de Sherbinin et al., 2011). The 2018 World Bank Groundswell Report (Rigaud et al., 2018) uses the CIESIN database to analyse internal displacement due to climate change. Peri & Sasahara (2019) exploit this data to examine how historical changes in temperature are related to net migration.

The scientific literature on climate change and migration is rapidly growing and recent contributions offer new opportunities to improve the understanding of these complex phenomena. Recent studies have made effort to quantify geographically the population exposed to climate change extreme events. This is done by overlaying spatially explicit population and climate change forecasts (see, for instance, Jones et al. 2015, Migali et al. 2018, Rohat et al. 2019, Smid et al. 2019). Other studies also provide forecasts of the number of people who will be moving as a response to adverse climatic events (Rigaud et al., 2018) and their destinations (Hauer, 2017). Most of these contributions rely on downscaling exercises of the world population that have been developed in relation to the Shared Socio-economic Pathways (SSP) scenarios and with climate change in mind (B Jones & O'Neill, 2016; Murakami & Yamagata, 2016).

Through the combination of population data and information on impacts of sea level rise, water scarcity, crop productivity and land degradation at high spatial resolution level (Borrelli et al., 2017; Sartori et al., 2019), it is possible to produce geographically detailed estimates of exposure for different combinations of SSP and Representative Concentration Pathway (RCP) scenarios. These estimates offer new possibilities to expand the mostly qualitative assessment contained in the last 2014 International Panel on Climate Change report with more detailed quantitative and geographical analyses. The first contribution in this direction is the 2018 World Bank Groundswell Report (Rigaud et al., 2018) that examines the impact of slow-onset climate change on internal displacement at a spatial resolution of about 14x14 km, by using advanced spatial modelling techniques.

[1] https://ec.europa.eu/eurostat/statistics-explained/pdfscache/2124.pdf.

In this context of growing interest and expanding literature on the climate change and migration nexus at high spatial resolution, the aim of this report is to provide new estimates of net migration spatially disaggregated. These estimates will be used in later stages to examine spatially the link between climate change, climate change impacts and net migration. Three novelties characterize the proposed net migration estimates when compared to the CIESIN database. First, the longer time horizon. Indeed, we provide net migration figures up to 2015 whereas the CIESIN database stopped in 2010. Second, the application of the new definition of Degree of Urbanization proposed by European Commission (Dijkstra and Poelman, 2014) and developed by the JRC *Atlas of the Human Planet 2018* (Corbane et al., 2018) – harmonized globally across countries. Notably, the new definition, proposed by a consortium of international organizations guided by the EU, has been recently endorsed by the United Nation Statistical Commission to enable international comparisons of cities, urban and rural areas[2]. This goes beyond the CIESIN database that is based on classifications of urban and rural not harmonized across countries. Third, from the methodological perspective, we propose a less complex approach than the one adopted in the CIESIN database. Indeed, as it will be clarified throughout the report, we address the issue of handling missing information at subnational level by making simplifying assumptions.

The report combines population data from the JRC Global Human Settlement Layer (GHSL) to demographic data from UN DESA to estimate five-year net migration from 1975 to 2015 at a spatial resolution of about 25 km and with a global coverage. The report applies a methodology based on a demographic indirect estimation technique – following the approach of De Sherbinin et al. (2012). Visualizations of net migration estimates are provided through an online data platform. A preliminary descriptive overview of the new estimates is also presented. In particular, the main general patterns of urban and rural net migration are described by looking at net migration in the first and in the last period considered (i.e. 1975-1980 and 2010-2015, respectively). In other words, we do not describe the trend over the reference period but we focus on two periods of time. We select the first and the last period to have the broadest overview. We do so to provide a first glimpse of the information that can be derived from our database. For instance, we observe that in most macro regions[3] worldwide, rural areas tend to have negative net migration (i.e. migration losses), while urban areas record positive net migration figures (i.e. migration gains). Moreover, net migration losses can be observed in rural areas in 1975-1980 and in 2010-2015, as it is the case of most macro regions in Asia. Despite differences across macro regions worldwide, urban areas have witnessed migration gains in both the first and the last period considered. This is the case, for instance, of Middle Africa and some European macro regions (Northern and Southern Europe).

Two data validation exercises are performed. First, new net migration estimates are compared to those provided by UN DESA 2019 World Population for all the countries worldwide. Second, we benchmark our estimates to Eurostat net migration figures at subnational (NUTS3) level for European countries. These comparison exercises confirm that there is a positive correlation between the new proposed estimates and official statistics on net migration, at both country and subnational level. Even though the magnitude of our estimates is different from the official

[2] https://ghsl.jrc.ec.europa.eu/degurba.php

[3] In the report we apply the classification of Geographic Regions of the UN Statistics Division (https://unstats.un.org/unsd/methodology/m49/).

net migration figures at subnational NUTS3 level, the ratio between our estimates and those from official statistics, on average, remains constant across subnational units.

The report is structured as follows. Section 2 reviews the most recent literature on the estimation of migration data at high spatial resolution. Section 3 explains the methodology and briefly presents the data used to produce estimates of net migration. Section 4 provides a concise overview of the net migration estimates. Two validation exercises are performed in Section 5. Section 6 concludes.

2 Related literature

Global and comparable data on migration at the country level are scant. Having information on migration at subnational level is even more complex. The most recent effort to address this data gap was achieved by the project of the Center for International Earth Science Information Network (CIESIN) and the Earth Institute at Columbia University. Indeed, they have produced global estimates of decadal net migration grids, from 1970 to 2010 (De Sherbinin, 2015; de Sherbinin et al., 2011, 2012).

By the application of indirect estimation techniques, they derive estimates of net migration grids at a spatial resolution of on a 30 arc-second (around 1 km) grid cell, based on the GRUMP (Global Rural Urban Mapping Project), Population World Count Grid and the HYDE database (History Database of the Global Environment) and demographic data retrieved from UN DESA Statistical Yearbook and the Demographic Health Surveys by urban/rural areas. The project shows how coastal ecosystems have experienced the highest positive net migration, from +30 million persons in 1970 to 82 million persons in 2000; while, mountain ecosystems have recorded the highest level of negative net migration over the four decades (126 million persons as total). Urbanisation, the redistribution of population from rural areas to cities, has been visible in most ecosystems, with accelerated rates of population growth in urban regions.

In line with the project, De Sherbinin et co-authors (De Sherbinin, 2015; de Sherbinin et al., 2011, 2012) use their estimates to analyse the patterns of net migration in different ecosystems and areas at risk of climatic hazards. Their analysis confirms that large rural areas are characterized by negative net migration, while smaller and typically urban areas tend to attract immigrants (i.e. have positive net migration). The analysis also suggests that over the decades considered people have generally moved from mountain and drought-prone areas to coastal ecosystems and area that are more at risk of floods and cyclones, with the exception of North America.

With respect to the demographic component, the approach of De Sherbinin et al. (2012) is based on data by urban/rural residence to account for different demographic patterns of fertility and mortality between urban and rural areas. Introducing information by urban/rural adds also a dimension of complexity due to the presence of missing data at this level. To address this issue, De Sherbinin et al. implement different imputation techniques. As significant contribution to the project, the authors collected fertility and mortality component at urban and rural level from UN Demographic Yearbooks and Demographic and Health Surveys and imputed missing values using two models: Multiple Imputation and Amelia. Both models fill missing observations as function of populations' socio-economic patterns.

In this respect, the most recent demographic literature is moving towards several different directions for the estimation of fertility and mortality indicators at subnational level. The increasing demand for data at the level of small areas has induced the development of a specific domain of studies: small domain or area estimation. This refers to the estimation of a population and its demographic behaviours for which reliable statistics cannot be produced due to limitations in available data (Huang & Hidiroglou, 2003; Rao & Molina, 2003). Two types of small area estimators are conventionally defined: direct and indirect estimators. The first type refers the value of estimated variables to the sample units in the domain of interest (e.g. the Horvitz-Thompson is the simplest direct estimator). The second type derives the value of estimated variables from the domain or time series observations (e.g. the synthetic estimator for a large area can be used as an indirect estimator for a small area, assuming that the large area can reflect the characteristics of the small ones). Area-level models, such as the Fay-Herriot model (Fay & Herriot, 1979) are often applied for small areas modelling area-level auxiliary variables. Small area methods attempt to exploit data attributes at larger areas to obtain estimators that can be used at disaggregated levels.

Recent contributions recommend the use of Bayesian estimation methods to estimate demographic indicators at the subnational level (Bijak and Briant 2016, Sevcikova et al. 2018). Modelling of point-referenced data becomes more difficult when regional aggregations are available at varying spatial resolutions (Wilson & Wakefield, 2020). This is the case when population census, which typically covers national levels, is available for certain periods and survey data, such as the Demographic and Heath Surveys, for smaller areas but with higher frequency. Therefore, the problem consists in making inference at a common spatial resolution (for instance, to tackle this issue Moraga et al., 2017, develop a stochastic partial different equation approach to relate two spatial levels of pollution data). Other approaches adopts methods to weight national representative survey data to get demographic indicators representative at the subnational level (Henderson et al., 2019). Additional problems may also derive from the changes over time in the definition of spatial aggregations (Lee et al., 2017).

The modelling of migration as demographic component is part of the population dynamics and projecting future trends at national level. Most of these studies rely on the Shared Socio-economic Pathways (SSP) scenarios (B Jones and O'Neill 2016; Murakami and Yamagata 2016; Kc & Lutz, 2017). Yet, regional and subregional events are even more relevant for understanding population exposure and vulnerability to climate change impacts; the inclusion of demographics within finer resolution requires sometimes the downscaling of national-scale information.

As it will be clarified in the Methodology section, this report adopts a simplified approach that overcomes the issue of missing data of subnational demographic indicators. As a direction for further research, births and deaths could be estimated at high spatial resolution level and with a global coverage by using one of the most recent approaches. These demographic data would constitute an extension and a refinement of those proposed in this report.

3 Methodology

3.1 Indirect estimation method

Literature reports two main approaches to estimate migration figures: - direct approach, which usually applies inference estimation technique on administrative data sources or surveys; - indirect approach, which usually applies residual methods using various and complementary data sources (Jandl, 2004). Our analysis adopts a residual indirect method to provide estimates of migration component at grid level for five-year intervals as in de Sherbinin et al. (2011, 2012b).

Specifically, in the indirect method the demographic balancing equation is formalized as follows (Wunsch & Termote, 1978):

$$P_{i,t+5} = P_{i,t} + \left(B_{i,t,t+5} - D_{i,t,t+5}\right) + (I_{i,t,t+5} - E_{i,t,t+5})$$

Whereas

$P_{i,t+5}$Population living in the grid cell i at the end of the reference period

$P_{i,t}$ Population living in the grid cell i at the beginning of the reference period

$B_{i,t,t+5}$ Births occurring in the grid cell i during the reference period $,t,t+5$

$D_{i,t,t+5}$Deaths occurring in the grid cell i during the reference period $,t,t+5$

$I_{i,t,t+5}$Immigrants to the grid cell i during the reference period $,t,t+5$

$E_{i,t,t+5}$Emigrants from the grid cell i during the reference period $,t,t+5$

From the equation, the population change derives from the difference between births and deaths during the observed interval (or natural increase) and the difference between in-migration and out-migration during the same period (or net migration), with respect to the selected territorial unit. That is the equivalent to say that the net migration corresponds to the difference between the population change and its natural increase, i.e.

$$I_{i,t,t+5} - E_{i,t,t+5} = \left(P_{i,t+5} - P_{i,t}\right) - \left(B_{i,t,t+5} - D_{i,t,t+5}\right)$$

The net migration obtained by this residual method is affected by several limitations (see Box 1 below). Despite all its limitations, the net migration remains nowadays the unique applicable indicator at the global level, which maximises the use of available official statistics and – at the same time - accounts for the specific spatial distribution of populations.

3.2 Data

To derive net migration estimates at grid cell levels, we apply the indirect method described above to two different data sources. For the population growth components ($P_{i,t+5} - P_{i,t}$) we use the JRC Global Human Settlement Layer (GHSL)[4]. This is a database that combines satellite and census data to provide information on global population at high spatial resolution. Specifically, it is based on the spatial distribution of built-up structures, derived from satellite data, and the spatial distribution of resident population, derived from census data. The GHSL has a global coverage and it contains information on human settlements and population in

[4] https://ghsl.jrc.ec.europa.eu/atlasOverview.php.

1975, 1990, 2000, and 2015. Importantly, it is also possible to distinguish the degree of urbanization of cells, according to the recent and harmonized definition provided by Dijkstra and Poelman (2014) and implemented in the JRC Atlas of the Human Planet 2018 (Corbane et al., 2018). For the demographic component $(B_{i,t,t+5} - D_{i,t,t+5})$, we use country level estimates of births[5] and deaths[6] following UN DESA Geographical system codification. The data source is the 2019 Revision of World Population Prospects (WPP)[7] produced by UN DESA Population Division.

Box 1. Net migration: definition and limitations

Net migration is defined as the difference between the number of immigrants and the number of emigrants[8]. When data on in-migration and out-migration are not available, net migration is obtained by comparing population increase over a given period of time with natural increase (births minus deaths) over the same period, i.e. through the indirect estimation method illustrated in the equation above (Section 3.1). Yet, doing so, the estimated net migration may be affected by inaccuracies of all components of the demographic equation, i.e. the population growth and the natural increase.

Several demographers have well explained limitations and expressed concerns against the use of net migration. For instance, Rogers, in his paper quite significantly entitled Requiem for the Net Migrant considers net migrant as "non existent" and Termote (1993) classifies the net migration as a "pure abstraction".

As a further caveat, it should be understood that, considering the population system composed by the selected population and the rest of the world, in this analysis, the net migration is the balance resulting from the migratory exchange between the targeted grid population and rest of geographical population system. This implies that no distinction can be made neither between regional movements (from the grid towards the same regional area) nor international movements (across international borders). Moreover, no distinction between the type of migratory movements (such as circular and return migration) is applicable.

3.3 Detailed methodology

We derive net migration estimates for each cell. Specifically, our approach consists of the following steps:

1 *Choice of spatial resolution of cells (25x25 km):* census population estimates, that are used as one of the data inputs for the GHSL, have different spatial resolution levels. For instance, in some countries the resolution is constituted by census areas of hundreds meters, while in other countries the resolution is lower, i.e. it refers to more aggregated areas, such as regions. The GHSL provides data at different levels (such as 1km). When choosing the spatial resolution for the estimation of our net migration data, with the aim of using it to study the link between climate change and migration, we face a trade-off between resolution and comparability across countries. On the one hand, higher resolution would allow for a more detailed spatial analysis. On the other hand, too detailed resolution would not ensure

[5] The number of births refers to five-year periods running from 1 July to 30 June of the initial and final years.
[6] The number of deaths refers to five-year periods running from 1 July to 30 June of the initial and final years.
[7] https://population.un.org/wpp/
[8] https://ec.europa.eu/eurostat/statistics-explained/pdfscache/2124.pdf

comparability and homogeneity of net migration across countries. We believe that a resolution of 25 km offers the best balance to this trade-off. Indeed, this resolution is quite common in geographical analyses of the link between climate change and migration (see, for instance, Xia et al., 2019) – which will be the ultimate goal of our future analyses.

2. ***Classification of cells by degree of urbanization (i.e. urban or rural)*** according to the new and harmonized definition of Degrees of Urbanization (Dijkstra and Poelman, 2014) used by Corbane et al. (2018). In particular, we classify as rural the cells defined in the GHSL (see Corbane et al., 2018; Florczyk et al., 2018) as: very low density rural, low density rural, rural cluster. We classify as urban the following cells: suburban or per-urban, semi-dense urban cluster, dense urban cluster, urban centre. It should be noted that the classification of the same cell may change over time[9]. Henceforth, we will show the data by degree of urbanization based on this classification.

3. Derivation of population growth for each cell $(i.e. P_{i,t+5} - P_{i,t})$: after having aggregated the population of the GHSL from 1 km to 25 km[10], we compute historical population changes for the three time periods available in the GHSL, i.e. the population change from 1975 to 1990, 1990 to 2000, and 2000 to 2015. To obtain population change also for the periods not available in the GHSL, we then proceed as follows. First, to model population change over the four time periods, an exponential growth population model is computed for each grid cell. Second, the coefficients from the exponential population growth model are used to derive the population change at grid level by five-year from 1970 to 2015.

4. Downscaling births and deaths $(i.e. B_{i,t,t+5} - D_{i,t,t+5})$*:* five-year country-level estimates of births and deaths - provided by UN DESA with a global coverage - are downscaled to higher resolution (25 km grid cell) according to the population distribution[11]. This downscaling exercise allows us to take the population structure of cells into account. In other words, country-level births and deaths are distributed according to the population living in each cell, be it an urban or rural cell. However, we do not take the possible variation of fertility and mortality in urban and rural areas into account. We are aware that this is a strong and simplifying assumption and its consequences are mentioned in Box 2 below. With respect to this assumption, our approach is different from the one of de Sherbinin et al. (2012). A concise comparison of the two approaches is provided in Box 2 below.

5. Estimation of 5-year net migration for each cell through the application of the indirect estimation method described above.

[9] For instance, in each country most of the cells are classified as rural in 2015. On average, in each country about 0.4% of cells are classified as urban in 2015. The percentage of cells classified as urban changes from 0.2% to 0.4% in the period 1975-2015.

[10] To map the global data we used an equal-area projection, the Mollweide pseudo cylindrical map projection. A spatial mask is applied for each country as correction for the cells overlapping the country boundaries.

[11] We used a dasymetric mapping approach.

Box 2. Similarities and differences with other approaches

The approach taken in this report is less complex and less refined than the one applied by de Sherbinin et al. (2012). Indeed, they use data on births/crude birth rates, deaths/crude death rates by urban/rural and implement imputation methods to tackle the issue of missing observations. Then, they derive a global database of rates of natural increase (from both observed and imputed values) that varies at the subnational level. Motivated by the empirical relationship between the rate of natural increase and the population density at the country level, they assume that there is a linear relationship between these two variables also at the grid cell level. Hence, they are able to derive the rate of natural increase in each cell as a function of the population density of the cell. There are two main issues related to this method: the missing observations for births and deaths by urban/rural in the official UN DESA statistics and the lack of uniform definitions of urban/rural used across countries.

In our simplified approach – that consists in the downscaling of country-level data on the basis of the population distribution in each cell - we overcome the issue of missing observations by urban/rural classification and the difference of this classification across countries. In relation to the missing observations by urban/rural, we decided to implement neither simple interpolation methods, nor more complex modelling approach as the one from de Sherbinin et al. (2011). The choice was dictated by the difficulty to make country-specific assumptions for those countries having only one value of births and deaths by urban/rural over time. More complex modelling approaches were also discarded: using socio-economic or demographic indicators to model missing values would create problems of recursion (or reverse causality) in the subsequent analysis of the relationship between climate change and net migration. In other words, this problem would arise since socio-economic variables used to impute missing values of net migration would be also used as control variables in regression models to investigate the relationship between climate change variables and net migration.

The strong and simplifying assumption underlying our approach is that, differently from de Sherbinin et al. (2012), we are not taking into account possible differences in fertility and mortality between urban and rural areas. This implies that our net migration at grid cell level is mainly driven by the population growth and it does not consider different behaviour of fertility and mortality in urban and rural areas. This assumption also implies that any under/overestimation of births and deaths along the urban/rural divide creates also a bias of net migration.

4 Results

In this section we give an overview of our net migration estimates and we present descriptively the main data patterns by degree of urbanization. It should be noted that this section aims at a preliminary descriptive and general overview of our database. As mentioned in the Introduction, the estimated net migration at high spatial resolution merely constitutes the first step of a broader JRC project with the scope to explore the relation between climate change and migration. A detailed geographical analysis of net migration data and related urbanization phenomena, as well as the examination of the climate change-migration nexus will be the subject of subsequent reports.

To appreciate and visualize the spatial variation of the estimated net migration, as well as the downscaling of the demographic data, a dashboard can be found here: https://bluehub.jrc.ec.europa.eu/migration/app/index.html#?state=5ee274cf0863ae3229115c38. The tool is composed of the global maps for all periods of five-year interval included in the analysis; precisely, maps show the net migration in absolute value of a cell of 25 km, which corresponds to a dot in the map-image resolution. For the sake of completeness, we also show the global maps with the natural increase for all the periods and calculated for the 25 km cells (as explained in Section 3.3). One example of the maps included in the dashboard is also provided below (see Figure 1).

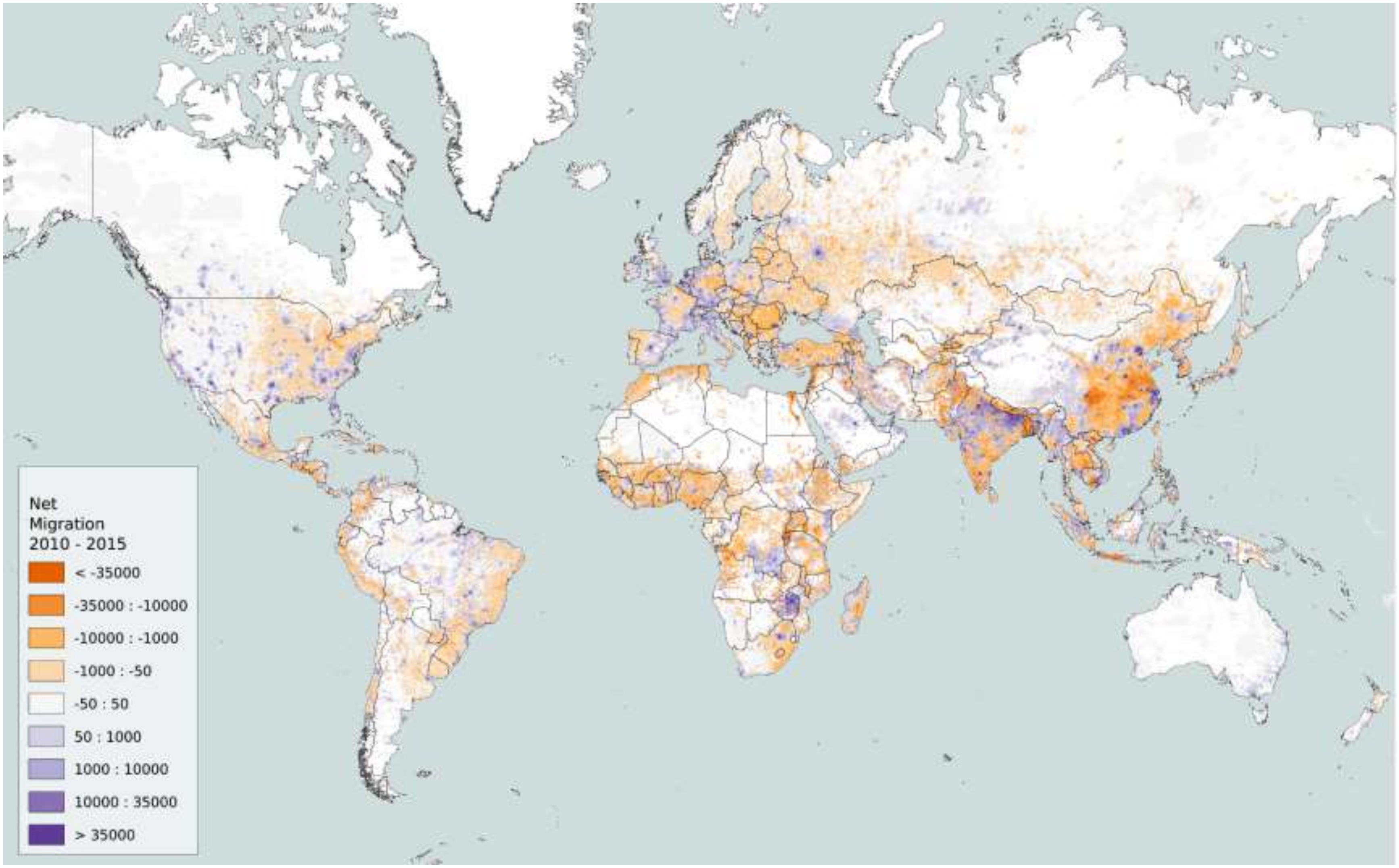
4.1 Net migration and degree of urbanization

As explained in the methodology section, we follow the globally harmonized definition of degrees of urbanization provided by Dijkstra and Poelman (2014) and developed by Corbane et al. (2018) to each cell. Table 1 below reports the net migration estimates by degree of urbanization and macro regions, according to the classification of Geographic Regions of the UN Statistics Division. In particular, to give a flavour of the data, we show the net migration for the initial and the final periods (i.e. 1975-1980 and 2010-2015, respectively). Overall, we observe that rural areas tend to experience net migration losses (i.e. have negative net migration), while urban areas tend to show migration gains (i.e. have positive net migration) for both periods and for most of the macro regions, as in de Sherbinin et al. (2012). Additionally, the following general patterns for the different macro regions can be observed.

African regions

Most African macro regions have witnessed negative rural net migration in the period 1975-1980, probably due to the emigration of people from rural areas. Migration losses can be observed in rural areas also in the period 2010-2015. Environmental degradation, including severe erosion, flooding and pollution, may have exacerbated populations living in areas where coastal degradation have also played an important toll (Croitoru et al., 2019). Overall, urban net migration in African macro regions is positive in both periods, thus signalling the attractiveness of urban areas. In 2010-2015, migration gains in urban areas can be observed

Figure 1 Net migration estimates, 2010-2015



for Eastern, Middle and Southern Africa. This stems mainly from the urbanization process in Angola and the Democratic Republic of Congo. According to the Socio economic pathway demographic projections, these areas are expected to continue to retain populations ranging from 100 million in 2010 to 350 million in 2050, under a more inclusive migration development scenario, and more than 450 million, under the pessimistic scenario (B Jones & O'Neill, 2016).

Asian regions

Migration gains in urban areas can be observed in most macro regions in Asia in 1975-1980 and 2010.2015. Gender urban migration patterns have also changed during these reference periods: for example, in Vietnam, female emigration from rural to urban has increased from 1990s, also as response to the economic reforms adopted in late 1980s (Thao & Agergaard, 2012). In other Asian countries, like the Philippines, migration has recorded increases in the proportion of female emigrants since the early 1970 (Melde, 2014). Net migration losses can be observed in rural areas in Central Asia, Eastern Asia, South-Eastern Asia in both periods considered.

European regions

Europe presents a slightly different picture as compared to the above-described general pattern of negative rural net migration. For instance, Northern Europe reports net migration gains in rural areas in 1975-1980 and 2010-2015 (of about 0.087 and 0.484 million, respectively). This means that the distribution of regional populations has remained relatively constant. The findings are confirmed by (Euorstat, 2000; Eurostat, 1978). Also in Western European countries[12], rural net migration is positive in both periods (and equal to 0.93 million and 1.37 million in 1975-1980 and 2010-2015, respectively). Stability in terms of migration patterns reported in these regions may also result from favourable environmental climate and ecologic conditions.

In Southern Europe, a change from negative to positive rural net migration is observed, which indicates a change of the migration patterns - from emigration to immigration - in the corresponding areas. This has clearly been the case of Italy. During the 1975-1980 period, population from the southern regions emigrated towards the northern regions, generating the detriment of these rural and agricultural regions (Eurostat, 1978). The proportion of movements has gradually decreased since 1990s, opening up for immigration in these areas (Livi-Bacci, 2010).

North American regions

Overall, rural areas in North America have recorded positive urban net migration in 1975-1980 and 2010-2015. McLeman (2009) pointed out that, given the social and cultural costs of migration in these areas, migration is rarely the first resort adaptation in the face of specific environmental stressors; therefore, a positive net migration should result from a multi-dimensional context, bridging the macro-economic scale patterns of population movements with cultural aspects and individual utility. By contrast, Central American regions reported a constant depopulation of rural areas. This pattern is evident in Mexico, which has been characterised by advanced urbanisation process.

[12] According to the UN classification of Geographic Regions, Western European countries include: Austria, Belgium, France, Germany, Liechtenstein, Luxembourg, Monaco, Netherlands, Switzerland.

During 2010-2015 period, positive rural net migration became higher in the Southern American region (with migration gains of about 0.5 million and 2.28 million in 1975-1980 and 2010-2015, respectively). This is in line with the so called new rurality. Several authors (such as Ramírez-Miranda, 2014) have argued that despite persistent rural trends, a new rurality characterized by the shift from an agrarian model, where the society is organized around primary activities, towards a society more linked with the urban markets, should be used to describe conditions of several Latin American regions (such as in El Salvador and Paraguay).

Table 1 Net migration in 1975-1980 and 2010-2015, by degree of urbanization and macro region

		Rural	**Urban**
Macro region	Period	Net migration (millions)	Net migration (millions)
Eastern Africa	1975-1980	3,963	0,621
	2010-2015	-5,59	0,118
Middle Africa	1975-1980	0,971	0,185
	2010-2015	-4,566	0,371
Northern Africa	1975-1980	0,655	0,532
	2010-2015	-3,918	-1,637
Southern Africa	1975-1980	-0,07	0,524
	2010-2015	-0,688	0,542
Western Africa	1975-1980	1,775	0,371
	2010-2015	-6,519	-0,488
Northern America	1975-1980	2,017	3,171
	2010-2015	4,347	2,768
Central America	1975-1980	-0,204	-1,38
	2010-2015	-0,098	-0,807
South America	1975-1980	0,501	0,638
	2010-2015	2,284	0,454
Caribbean	1975-1980	1,191	0,105
	2010-2015	1,611	0,134
Central Asia	1975-1980	-0,101	0,064
	2010-2015	-1,345	-0,455
Eastern Asia	1975-1980	-2,164	10,075
	2010-2015	-12,494	10,099
South-Eastern Asia	1975-1980	-1,175	2,707
	2010-2015	-4,688	-0,027
Southern Asia	1975-1980	14,589	-4,17
	2010-2015	-1,15	-0,506
Western Asia	1975-1980	0,463	1,69
	2010-2015	0,718	1,545
Eastern Europe	1975-1980	-1,739	0,929
	2010-2015	-2,451	0,75
Northern Europe	1975-1980	0,087	0,325
	2010-2015	0,484	0,618
Southern Europe	1975-1980	-1,329	0,054
	2010-2015	1,778	0,98
Western Europe	1975-1980	0,93	0,73
	2010-2015	1,37	0,729

5 Evaluation of the results

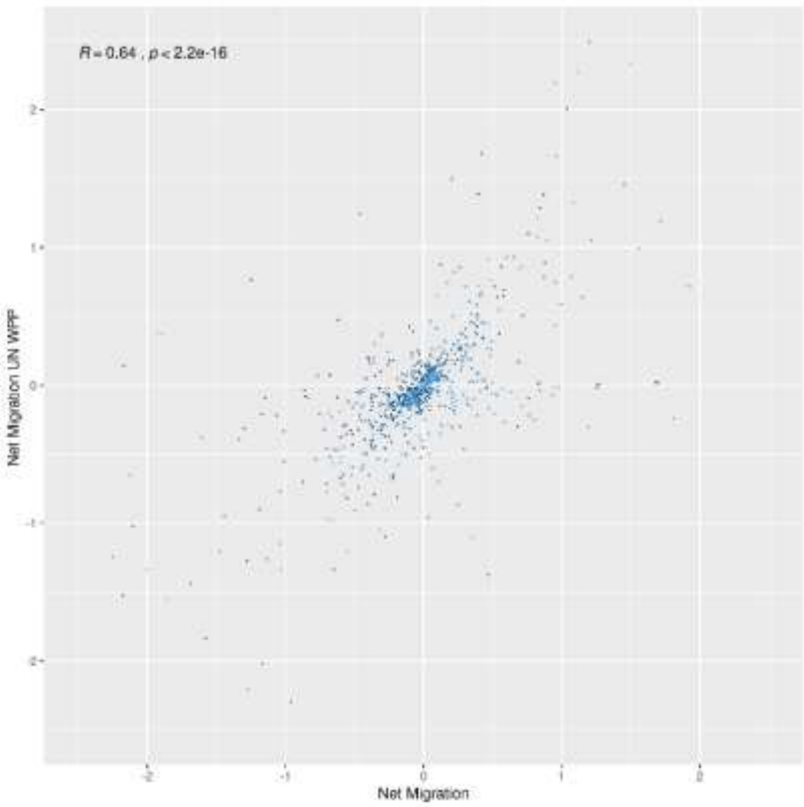
5.1 Validation

In this section we evaluate our database by comparing it to data from different official statistics. The ideal solution would be to compare our net migration estimates at high spatial resolution (25 km) to official statistics data with the same spatial resolution. However, this is not possible since official statistics on net migration at such a granular spatial resolution are not available worldwide. Therefore, we are forced to carry-out the validation exercise by aggregating our net migration estimates at a lower spatial resolution level to make them comparable to official statistics at the same lower spatial level. In particular, we proceed with the following two validation exercises. First, we compare to country-level net migration figures from UN DESA 2019 World Population Prospects for all the countries worldwide[13]. Second, we compare to subnational (i.e. NUTS3 level) net migration figures from Eurostat for European countries.

Validation with UN DESA country-level data

The objective of this validation is to provide an overview of how our estimated net migration compares to UN DESA World Population Prospects country-level estimates of net migration. Figure 2 shows the scatterplot of our net migration estimates (horizontal axis) and those from UN DESA World Population Prospects (vertical axis). Each dot represents the five-year country net migration. All countries worldwide and all the five-year intervals from 1980 to 2010 are included. As expected, we find positive and significant correlation (equal to 0.64) between our net migration estimates at country-level and those from UN DESA.

Figure 2 Net migration estimates compared to UN World Population Prospects country-level net migration estimates, 1980-2010



Notes: net migration (expressed in millions). Each dot represents the country-level level net migration estimates in the two datasets. Darker dots refer to the most recent five-year periods.

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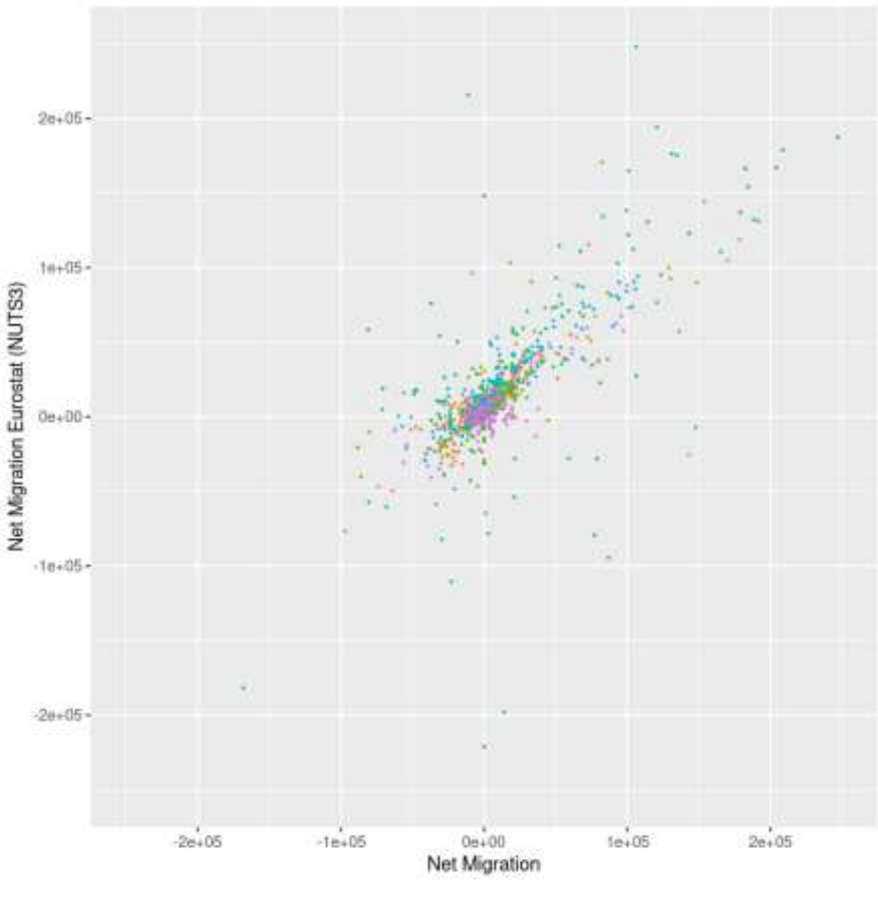
[13] https://population.un.org/wpp/

Validation with EUROSTAT NUTS3-level data

As a second validation exercise, we compare net migration estimates to those from Eurostat regional demographic statistics[14] at a level of spatial disaggregation corresponding to NUTS3. It should be stressed that the comparison is possible only after 2000[15]. Indeed, even though the NUTS classification was set up by Eurostat at the beginning of the 1970s, the provision of data at NUTS level by EU member states was based on gentlemen's agreements for about thirty years[16]. In other words, for most of the countries NUTS3 data are not available before 2000, hence the data validation exercise for all the EU for this period is not possible.

Figure 3 represents the scatter between net migration estimates at NUTS3 level from Eurostat (vertical axis) and our estimates (horizontal axis). The graph includes European countries[17] and refers to the period 2000-2015. Each dot represents a NUTS3 region. Also in this case, and as expected, we find a positive and significant correlation (equal to 0.62).

Figure 3 Net migration estimates compared to Eurostat NUTS3-level net migration estimates, 2000-2015



Notes: net migration (expressed in hundred thousands). Each dot represents the NUTS3-level net migration estimates in the two datasets. The colours indicate different EU countries.

Figure 3 also indicates that there are some differences in terms of magnitude between our net migration estimates at NUTS3-level and those from Eurostat. Despite the differences,

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[14] Specifically, we compare to Eurostat regional demographic database 'Population change - Demographic balance and crude rates at regional level (NUTS 3) [demo_r_gind3]'; variable 'crude rate of net migration plus statistical adjustment'. Importantly, this Eurostat net migration variable is derived through indirect estimation method, as in our estimates. It should also be noted that to compare NUTS3 regions, we use a grid resolution of 4 km and then sum up the values to the NUTS3 polygons. The comparison adopts Eurostat 2016 NUTS classification.

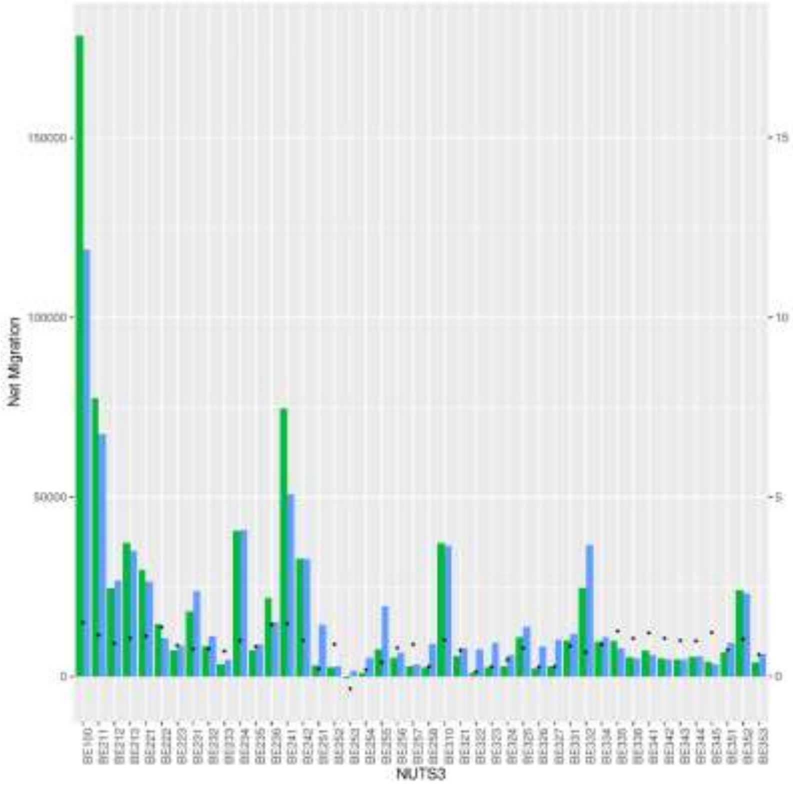
[15] https://ec.europa.eu/eurostat/cache/metadata/en/demo_r_gind3_esms.htm

[16] https://ec.europa.eu/eurostat/web/nuts/history

[17] EU 27, Switzerland and Norway included, Romania excluded due to some data inconsistencies.

the ratio between our estimates and the official ones from Eurostat tends to be, on average, equal across NUTS3. For the sake of example, Figure 4 represents the ratio, for each NUTS3, between our net migration estimates and those from Eurostat for the case of Belgium.

Figure 4 Net migration estimates compared to Eurostat NUTS3 net migration estimates and ratio between them. Belgium, 2000-2015



Notes: net migration estimates: Eurostat (blue bars) and our estimates (green bar). The dots represent the ratio between our net migration estimates and Eurostat estimates, for each NUTS3.

Overall, the validation exercises with official statistics suggest that the country-level aggregation of net migration of 25 km resolution is coherent with UN DESA Population Prospects estimates of country-level net migration. When focusing on Europe, where estimates of net migration are available at NUTS3 since 2000, we also find that the regional aggregation of our net migration estimates positively correlates with Eurostat data. Despite some differences in the magnitude of net migration for some EU NUTS3, the analysis shows that the ratio between our estimates and those from official statistics is, on average, constant across subnational units.

6 Conclusion

This report has provided new five-year net migration estimates from 1975 to 2015 at a spatial resolution of about 25 km and with global coverage. Net migration is obtained by combining population data from the JRC GHSL and demographic data from UN DESA 2019 World Population Prospects. An indirect estimation method is applied. Particular attention is given to the new classification of Degree of Urbanization recently proposed by the European Commission (Dijkstra & Hugo Poelman, 2014), implemented by the JRC (Corbane et al., 2018) and endorsed by the United Nations Statistical Commission. Notably, the new globally harmonized classification allows us to not only estimate net migration separately for urban and rural areas, but also – and most importantly – to obtain urban/rural net migration comparable across countries.

The most important features of the new JRC net migration estimates are their comparability with respect to urban/rural areas, their global coverage as well as their spatial disaggregation. The main limitation is that they are obtained as a residual, through an indirect estimation method. Another limitation stems from the fact that the proposed methodology takes only the distribution of populations in urban and rural areas into account, but not the possible differences in demographic behaviour (fertility, mortality) between these areas.

A preliminary overview of the database shows important patterns of net migration in rural and urban areas. In most macro regions worldwide, rural areas tend to experience net migration losses both in 1975-1980 and 2010-2015. Instead, migration gains are observed in urban areas, that, overall, have witnessed positive net migration in both periods considered.

Two validation exercises of the new database are proposed. The comparison to both country and subnational net migration figures from official UN and Eurostat statistics, respectively, shows that the proposed estimates positively correlates to official data. Despite differences in magnitude of our estimates as compared to European subnational NUTS3 net migration figures, the ratio between our estimates and the official ones tend to be constant across subnational units.

Importantly, the new JRC net migration estimates will be used for a broader JRC project aimed at quantifying climate change induced migration at a high spatial resolution. They may also open avenues for further research aimed at addressing the challenges and providing refined estimates of demographic components at high spatial resolution level.

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